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Subclass Discriminant Analysis based Myoelectric Hand Motion Recognition

Dalin Zhou, Yinfeng Fang, Zhaojie Ju and Honghai Liu

Abstract — **Control of prosthetic hands and other upper-limb assistive device for rehabilitation relies on the premise that users' hand motion intention is accurately recognised. Among all the feasible modalities, myoelectric hand motion recognition has been most adopted yet suffers from its intrinsic day-to-day changes. Despite the promising accuracy achieved by pattern recognition approaches in intra-day tests, the inter-day performance deteriorates in long-term use. From the users' perspective, it is desired that the hand motion recognition accuracy improves while the burden of user training is confined within 1 or 2 days. In this paper, subclass discriminant analysis is applied instead of conventional linear discriminant analysis for myoelectric hand motion recognition for long-term use. The evaluation results on 10 days' myoelectric data captured from 6 subjects show that the subclass division contributes to improved inter-day recognition accuracy with limited training data.**

I. Introduction

For prosthesis and other upper-limb assistive device users, good intuitiveness, high success rate, low latency and limited adaptation cost of the devices are the prior properties to be fulfilled [1]. In details, the premise of an ideal control is crafted by the accurate recognition of users' intention, the imperceptible delay between the execution of the mechanical extremity and the employment of users' residual limb, and their consistent feasibility for long-term use. Among various feasible approaches, electromyography (EMG) based pattern recognition for prosthetic hand control has been the most widely investigated one for its most promising performance [2]. The aim of such methodology is to distinguish users' intention of hand movement through classifying the patterns extracted from EMG signals captured during forearm muscle contractions. Increasingly high accuracy and improved robustness have been frequently published within the framework of pattern recognition in academia in terms of development of classifiers [3] and features [4]. And the superiority of pattern recognition based solutions in clinical scenarios has been stated in various recent research [5-7]. However, the intrinsic randomness of the EMG signals contributes to a degraded performance in long-term use, which has been addressed by researchers [8-10] yet not fully accommodated.

Reports have shown that long-term use will deteriorate the hand motion recognition accuracy across multiple days. Various factors that affect the consistency of long-term EMG signals have been taken into account like fatigue and electrode shift [11]. The deterioration of inter-day performance leads to the requirement of everyday training effort from the users to adjust the applied recognition algorithm. The burden of re-training and re-calibration prevents the current research prototypes from being applied in clinical settings. Less or no re-training depends on better priori knowledge of the potential invariance and inter-day relation of EMG during long-term use. The inter-day performance of EMG based hand motion recognition is improvable under the assumption that invariance and inter-day relation could be extracted from EMG, which in turn is governed by jointly improved feature selection and classifier design. Mature classification approaches like linear discriminant analysis (LDA) have been widely applied in EMG based hand motion recognition in combination with the classic Hudgins' time domain features [12] together with autoregressive coefficients (TDAR), yet not able to fully exploit the invariant part and transfer it to inter-day use. Despite the efforts in an adaptive way to accommodate the unseen data in long-term use [3,10], the improved exploitation of the seen data is rarely published. Thus it is timely and challenging to propose suitable pattern recognition approaches for long-term use which can be identified in the development of robust classifiers for inter-day scenarios. A subclass division based discriminant analysis framework is adopted in this paper to address the aforementioned challenges.

The rest of this paper is organised as follows. Myoelectric hand motion recognition is briefly introduced in Section II with an emphasis on the pattern recognition based solutions. The adopted subclass division based discriminant analysis is explained in details in Section III. And the experiment setup and evaluation results are provided in Section IV. Finally this paper is concluded in Section V with discussion.

II. Pattern Recognition based Myoelectric Hand Motion Recognition

To date, let alone the numerous manifestations that represent muscle activity, EMG remains the main equipped sensing modality for muscular activity sensing in the active control of almost every commercial upper limb prosthesis and exoskeleton for active limb motor function restoration. Pattern recognition approaches have been mostly investigated for their promising accuracy in the recognition of dexterous motion templates. A typical flowchart of pattern recognition based myoelectric hand motion recognition is shown in Fig. 1. The EMG signals are first preprocessed and segmented. Within each segment, a decision is generated through the routine of a pattern recognition approach comprising the feature extraction and classification.

Dalin Zhou is with the School of Computing, University of Portsmouth, PO1 3HE, UK (phone: +44-7835261646; e-mail: dalin.zhou@port.ac.uk).
Yinfeng Fang is with Hangzhou Dianzi University, 310018, China. (e-mail: yinfeng.fang@hdu.edu.cn).
Zhaojie Ju is with the School of Computing, University of Portsmouth, PO1 3HE, UK (e-mail: zhaojie.ju@port.ac.uk).
Honghai Liu is with the School of Computing, University of Portsmouth, PO1 3HE, UK (e-mail: honghai.liu@port.ac.uk).

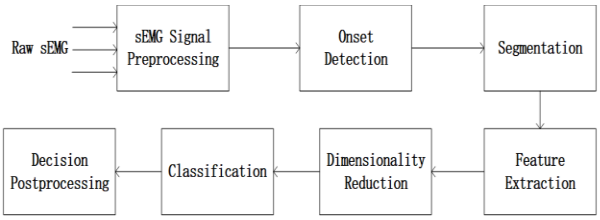

Figure 1. A typical flowchart of pattern recognition based myoelectric hand motion recognition

Classifier design plays an important role in pattern recognition based applications. Numerous classification strategies like LDA, SVM and GMM together with their modifications have been applied in myoelectric hand motion recognition. Among all the conventional recognition frameworks, LDA has been employed in the EMG based hand motion recognition for decades and remains the most important baseline for its robust performance in academic research. Liu et al. [10] addressed the reduction of user re-training while preserving acceptable inter-day recognition accuracy by using LDA with an optimised projection. Vidovic et al. [13] employed supervised adaptation to calibrate the model for inter-day use on both able-bodied subjects and amputees. The aforementioned discriminant analysis methods are mostly based on the assumption that each class is represented by a single cluster. However, separated subclasses are possibly formed because of the nonstationary and stochastic nature of sEMG signals. Overlapping subclasses among predefined classes could go against the assumptions embedded in some classification methods. For example, the distribution of pooled samples might not meet the assumption of having a common covariance matrix but different means for LDA. The potential of subclass division in the cross-day settings has not been addressed yet regardless of the widely developed modifications of LDA. Despite the intensive research interest in discriminant analysis based myoelectric hand motion recognition, the development of classifiers with a specific focus on the inter-day hand motion recognition for long-term use is rarely seen, not mentioning the emphasis on various adequateness of training samples in comparison to the testing ones. The inter-day overlapping problem is addressed in this paper by utilising the subclass division prior to discriminant analysis to exploit its advantageous capability in myoelectric hand motion recognition with inadequate training data from 1 or 2 days and the testing data from unseen days.

III. Subclass Division based Discriminant Analysis

In our preliminary work [14], the effectiveness of subclass division has been proved on the force based granular modeling for grasp recognition, where the EMG signals and forces of hand grasps were captured synchronously. The grasping force was introduced by the incorporation of an additional force sensor to the EMG capturing system. And the classes of hand motions were enriched by an additional attribute describing the force levels. Let alone the accurately categorised samples, the misclassification among subclasses that belong to the same class will contribute to the improved correct classification through a mapping into the original classes at last.

Despite the improved recognition accuracy, the force driven subclass division is based on an additional attribute of force utilising extra sensory information at an ideal setting and does not reflect the real daily life scenarios, where human-object interaction is conducted without the force sensing. Thus it is essential to conduct the subclass division for hand motion recognition using solely EMG signals across multiple days with inadequate training data, whose subclasses are shaped by the inter-day changes of EMG characteristics and electrode shift caused by donning/doffing in long-term use. An intuitive approach is the implicit subclass division that utilises the subclass information without enlarging the class labels in a fining and coarsening scheme, and is realised in the discriminant analysis directly. The discriminant analysis based algorithms classify the samples with a projection of the original data into a reduced subspace with an optimised separability by simultaneously maximising the between-class distance and minimising the within-class distance. Accordingly, a general criterion of separation for most discriminant analysis algorithms is defined in (1).

$$S = \frac{|\omega^T S_b \omega|}{|\omega^T S_w \omega|} \tag{1}$$

Where S_w and S_b are the scatter matrices of within-class distance and between-class distance respectively, and ω represents the direction for projection. The discriminant analysis aims to find an optimal projection direction by maximising S. Conventionally the within-class scatter matrix is defined in (2).

$$S_w = \frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{N_i}(x_{ij} - u_i)(x_{ij} - u_i)^T \tag{2}$$

Where N is the total number of samples, C is the number of classes, N_i is the number of samples that belong to class i, x_{ij} is the j-th sample within the class i, and u_i is the mean centre of class i.

An integration of subclass division into the projection determination is utilised instead of using two independent subclass division and linear discriminant stages. The subclass discriminant analysis (SDA) algorithm proposed by Zhu et al. [15] is the first discriminant analysis considering the distance between subclasses instead of the distance between classes. The idea is adopted in combination with the nearest neighbour based division criterion in this paper to find the most convenient division of each class into multiple subclasses in an exhaustive scheme.

The between-class scatter matrix is defined in (3).

$$S_b = \sum_{i=1}^{C}\sum_{p=1}^{c_i}\sum_{j=i+1}^{C}\sum_{q=1}^{c_j}\frac{n_{ip}}{N_i}\frac{n_{jq}}{N_j}(u_{ip} - u_{jq})(u_{ip} - u_{jq})^T \tag{3}$$

where C is the number of classes, c_i is the number of subclasses within the class i, N_i and N_j are the number of samples belonging to class i and j respectively, N_{ip} is the number of samples belonging to the subclass p of class i, and u_{ip} is the mean centre of subclass p of class i. The distance between subclasses is utilised instead of the distance between classes to extract the distribution information of subclasses attributed to the overlapping classes in long-term use.

Conventionally, once the scatter matrices are acquired, the projection direction is found to linearly separate the pooled data following the generalised eigenvalue decomposition as

$$S_b W = S_w W \Lambda \tag{4}$$

Where W is the projection matrix whose columns are formed by the right eigenvectors and Λ is the diagonal matrix whose diagonal elements are corresponding eigenvalues. The first k columns of W with the greatest magnitude of eigenvalues are selected to form the projection matrix $W^k$for a k+1-class classification problem.

Based on the definition in (3), the further calculation of projection direction requires a determined subclass division number of each class. The strategy for seeking optimal subclass divisions with the leave-one-trial-out test is adopted on the pooled dataset for both training and testing with only one trial of samples excluded to achieve the global optimum. In this paper, the selection of separate training and testing samples is adopted to address the inter-day and long-term use instead of solely considering the intra-day use. Specifically, the training samples from each class are first divided into subclasses according to their inter-sample distances. The nearest neighbour method is adopted in the distance sorting, which measures the Euclidean distance between the two samples x_{ip} and x_{iq} within the class i to determine their subclass category. Then SDA classifiers using different subclass division choices are compared with the recognition accuracy on the testing data. The one with the highest accuracy is finally selected for further validation on the subclass division number. And the subclass division driven discriminant analysis is then conducted by solving (4).

IV. Experiments

A. Data Acquisition

In the absence of a well acknowledged benchmark for long-term inter-day myoelectric hand motion recognition, the evaluation in this paper is conducted on a locally captured dataset. A customised 16-channel EMG capturing system developed by [16] is adopted for the EMG signal capturing. The 16 bi-polar electrodes are formed by sharing each electrode with two neighbouring channels, and embedded in a stretchable sleeve to cover both the anterior and posterior compartments of forearm muscles with an optimised zig layout. The acquisition system is equipped with a sampling frequency of 1000 Hz, a gain of 3000 and an ADC resolution of 12 bits. The captured EMG signals are bandpass filtered between 20 Hz and 500 Hz by a Butterworth filter and separated from the power line noise with a notch filter. Another empty sleeve is used to cover the electrode sleeve to ensure a firm contact between the electrodes and the skin surface to alleviate movement artefacts. The digitalised EMG signals are transmitted to a personal computer via USB connection for data recording and processing. A graphical user interface is designed to display the motion hints and corresponding 16-channel filtered EMG signals.

A total of 13 hand motion candidates shown in Fig. 2 are included in this database, comprising 3 basic palm movements of hand rest (HR), hand open (HO) and hand close (HC), 4 wrist movements of wrist flexion (WF), wrist extension (WE), ulnar flexion (UF) and radial flexion (RF), 2 forearm movements of pronation (PR) and supination (SU), and 4 basic grasp types of fine pinch (FP), key pinch (KP), spherical grasp (SG) and cylindrical grasp (CG). A total of 6 able-bodied subjects (2 females and 4 males) are recruited in the experiment. The subjects are all with intact limb motor function and do no suffer from any neurological or muscular disorders. The subjects are all unfamiliar with the prosthetic control and EMG based hand motion recognition. This experiment is approved by the ethics committee of University of Portsmouth with written informed consent obtained from all subjects.

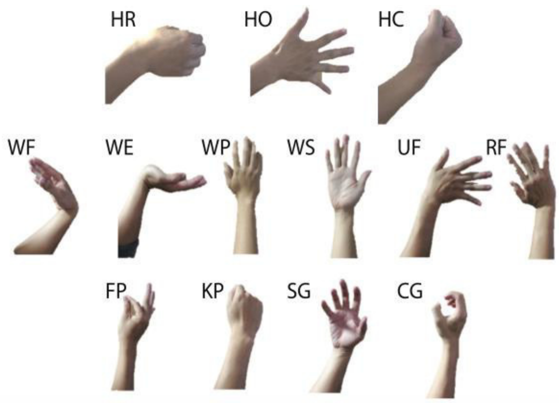

Figure 2. Hand motion candidates for recognition

The user training protocol proposed in our previous work [17] is adopted to improve the consistency of EMG patterns from users' voluntary hand motions prior to their participation in the on-site database building. It has been proved that the clustering-feedback user contributes to a consistent online performance, which leads to a more reliable evaluation result. The user training protocol encourages the subjects to adjust their muscle contraction and force control in each intra-day trial, which removes the adverse artefacts of voluntary contraction and confines the variation of EMG signals to inter-day physiological changes.

B. Experiment Results

The comparison of SDA and LDA based solutions on inter-day use is depicted in Fig. 3 and Fig. 4. The data of 6 subjects performing 13 hand motions in consecutive 10 days are adopted. The classifiers are trained by 1 day's and 2 day's data respectively and tested on the rest days' data using the same group of the 128-dimensional TDAR features, which means the recognition is totally conducted on the unseen data captured in novel days. The number of subclasses is set equal among all classes as a constraint. The average recognition accuracy increases with slight improvement utilising SDA instead of LDA. In details, an improvement of recognition accuracy across the subjects can be seen for the situation with inadequate training of 1 day, and 9 days' totally unseen data for testing, which supports the implicit incorporation of subclass division among multiple trials when inadequate training data are provided.

A detailed numerical comparison of the recognition accuracy and corresponding numbers of testing samples is shown in Table I. It is seen that the recognition accuracy increases by a large extent of around 10% when a new day's data is included for the training which aligns with the intuition. Regardless of the enriched training of 2 days' data, the total samples are still inadequate when compared to the 8 days' unseen data for prediction.

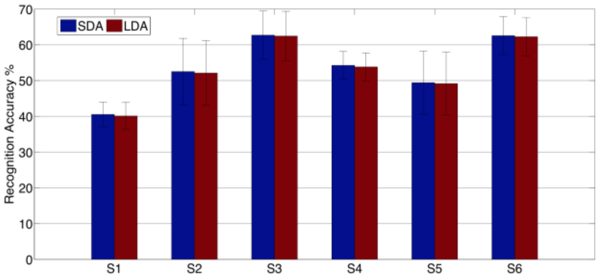

Figure 3. Recognition accuracy with training on 1 day's data

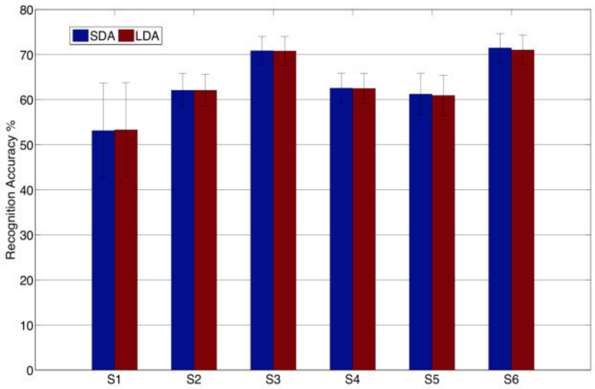

Figure 4. Recognition accuracy with training on 2 days' data

TABLE I. COMPARISON OF SDA AND LDA BASED INTER-DAY MYOELECTRIC HAND MOTION RECOGNITION ACCURACY

Subjects	Training on 1 day		Training on 2 days	
	LDA (%)	*SDA(%)*	*LDA (%)*	*SDA(%)*
1	40.11±3.79	40.54±3.46	53.29±10.50	53.12±10.51
2	52.11±9.06	52.53±9.28	62.08±3.50	62.08±3.70
3	62.46±6.91	62.72±6.76	70.78±3.25	70.85±3.18
4	53.83±3.89	54.26±3.88	62.48±3.32	62.56±3.31
5	49.17±8.82	49.43±8.83	60.93±4.45	61.24±4.62
6	62.27±5.37	62.58±5.29	71.03±3.28	71.47±3.18
Mean	**53.32**	**53.67**	**63.43**	**63.55**

V. CONCLUSION

In this paper, the subclass division based discriminant analysis is applied in the long-term and inter-day myoelectric hand motion recognition. And the results gained from the experiments on 6 able-bodied subjects in consecutive 10 days comply with the intuitive idea that the extraction of subclasses among multiple trials and multiple days will lead to a better distinguishability of the EMG signals without increasing the burden of user training.

It is worth noting that the experiments are only conducted on healthy subjects in this paper. A potential discrepancy may reside in the different motor function conditions between amputated users and able-bodied subjects. Further validation on targeted prosthesis and assistive device users is required. And the feasibility of the subclass division methods on inter-subject scenarios is also worth investigating in the future.

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